

# Spectral Graph Theory

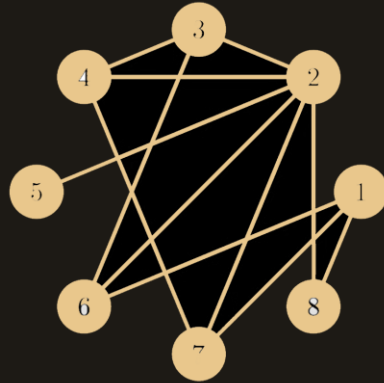
## An Invitation

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$\int$  Ron  
&  
Math

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# Eigenvalues of a Graph?



$$\vec{v} = \lambda \vec{v}$$

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# OUTLINE

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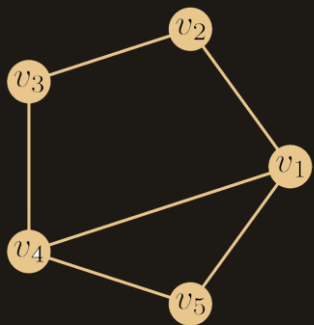
GRAPH LAPLACIAN  
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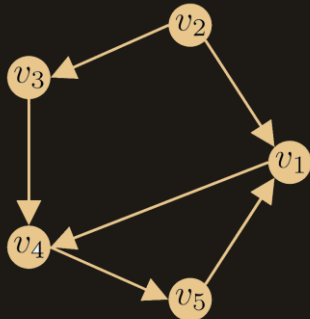
# Basic Graph Theory



$$G = (V, E)$$

$$V = \{v_1, v_2, v_3, v_4, v_5\}$$

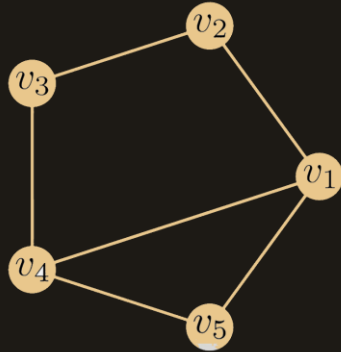
$$E = \{(v_1, v_2), (v_1, v_4), (v_2, v_3), \dots, (v_5, v_1)\}$$



$$e_{1,2} = (v_1, v_2)$$

$$e_{2,1} = (v_2, v_1) \neq e_{1,2}$$

# Degrees of Vertices and Connectivity



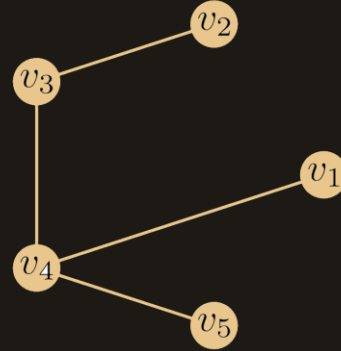
$$d(v_1) = 3$$

$$d(v_2) = 2$$

$$d(v_3) = 2$$

$$d(v_4) = 3$$

$$d(v_5) = 2$$



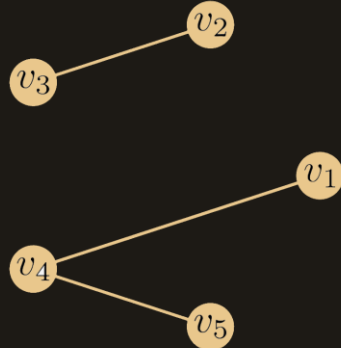
$$d(v_1) = 1$$

$$d(v_2) = 1$$

$$d(v_3) = 2$$

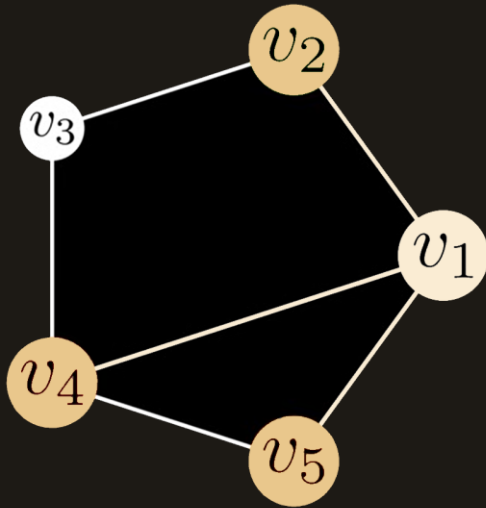
$$d(v_4) = 3$$

$$d(v_5) = 1$$



The graph has 2 connected components, but the graph itself is no longer connected.

# Adjacency and Degree Matrices



$$A = \begin{pmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

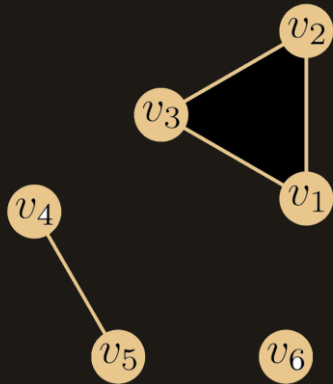
$$A_{i,j} = \begin{cases} 1 & \text{if } (v_i, v_j) \in E \\ 0 & \text{otherwise} \end{cases}$$

$$D = \begin{pmatrix} 3 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 2 \end{pmatrix}$$

$$D_{i,j} = \begin{cases} d(v_i) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

- Both matrices are real symmetric

# Disconnected graphs have distinct block structure of adjacency matrix



$$A: \begin{pmatrix} \boxed{\begin{matrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{matrix}} & \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} \\ \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \boxed{\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix}} & \begin{matrix} 0 \\ 0 \\ 0 \end{matrix} \\ \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{matrix} & \boxed{0} \end{pmatrix}$$

- This has interesting impact on eigenvalues and eigenvectors





# Spectral Theory of Graphs

In mathematics, spectral theory is an inclusive term for theories extending the eigenvector and eigenvalue theory of a single square matrix to a much broader theory of the structure of operators in a variety of mathematical spaces.

Source: Wikipedia





Real symmetric matrices are guaranteed to be diagonalizable with real eigenvalues

$$\begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{pmatrix} = \underbrace{\begin{pmatrix} -0.44 & -0.71 & 0.56 & 0.0 \\ -0.56 & 0.0 & -0.44 & -0.71 \\ -0.56 & 0.0 & -0.44 & 0.71 \\ -0.44 & 0.71 & 0.56 & 0.0 \end{pmatrix}}_P \underbrace{\begin{pmatrix} 2.6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -1.6 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}}_{\Lambda} \underbrace{\begin{pmatrix} -0.44 & -0.71 & 0.56 & 0.0 \\ -0.56 & 0.0 & -0.44 & -0.71 \\ -0.56 & 0.0 & -0.44 & 0.71 \\ -0.44 & 0.71 & 0.56 & 0.0 \end{pmatrix}^{-1}}_{P^{-1}}$$

# Addition and subtraction retain real symmetric property

$$\underbrace{\begin{pmatrix} 2 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 2 \end{pmatrix}}_D - \underbrace{\begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{pmatrix}}_A = \underbrace{\begin{pmatrix} 2 & -1 & -1 & 0 \\ -1 & 3 & -1 & -1 \\ -1 & -1 & 3 & -1 \\ 0 & -1 & -1 & 2 \end{pmatrix}}_{\text{Laplacian matrix: } \mathbf{L}}$$

$$L_{ij} = \begin{cases} d(v_i) & \text{if } i = j \\ -1 & \text{if } i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise} \end{cases}$$

# Graph Laplacian

$$L = D - A$$

$$(Lf)_i = \sum_{j, i \sim j} (f(i) - f(j))$$

$$Lf = \lambda f$$

$$\lambda = f^t L f$$

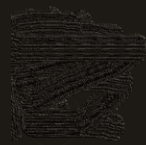
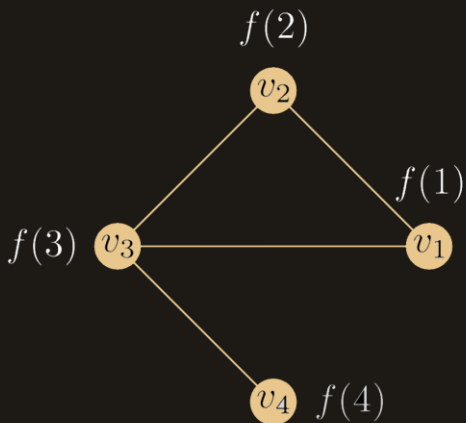
$$\lambda = f^t L f = \sum_i f(i) (Lf)_i$$

$$\lambda = \sum_i (f(i) \sum_{j, i \sim j} (f(i) - f(j)))$$

- **f is a function on graph vertices and an eigenvector of Laplacian**

# Graph Laplacian

$$\lambda = \sum_i (f(i) \sum_{j, i \sim j} (f(i) - f(j)))$$



$$\begin{aligned} & f(1)(f(1) - f(2)) + f(1)(f(1) - f(3)) \\ & + \\ & f(2)(f(2) - f(1)) + f(2)(f(2) - f(3)) \\ & + \\ & f(3)(f(3) - f(1)) + f(3)(f(3) - f(2)) + f(3)(f(3) - f(4)) \\ & + \\ & f(4)(f(4) - f(3)) \end{aligned}$$

- **f is a vector and a function?**

# Graph Laplacian



$$\begin{aligned}
 & f(1)(f(1) - f(2)) + f(1)(f(1) - f(3)) && (f(1) - f(2))^2 \\
 & + && + \\
 & f(2)(f(2) - f(1)) + f(2)(f(2) - f(3)) && (f(1) - f(3))^2 \\
 & + && + \\
 & f(3)(f(3) - f(1)) + f(3)(f(3) - f(2)) + f(3)(f(3) - f(4)) && (f(2) - f(3))^2 \\
 & + && + \\
 & f(4)(f(4) - f(3)) && (f(3) - f(4))^2
 \end{aligned}$$

$$\lambda = \sum_i (f(i) \sum_{j, i \sim j} (f(i) - f(j))) = \sum_{i < j, i \sim j} (f(i) - f(j))^2$$

# Graph Laplacian

$$\lambda = \sum_{i < j, i \sim j} \boxed{(f(i) - f(j))^2}$$

Observation 1:  $L$  is positive semi-definite.

$$\lambda_i \geq 0 \quad \forall i$$

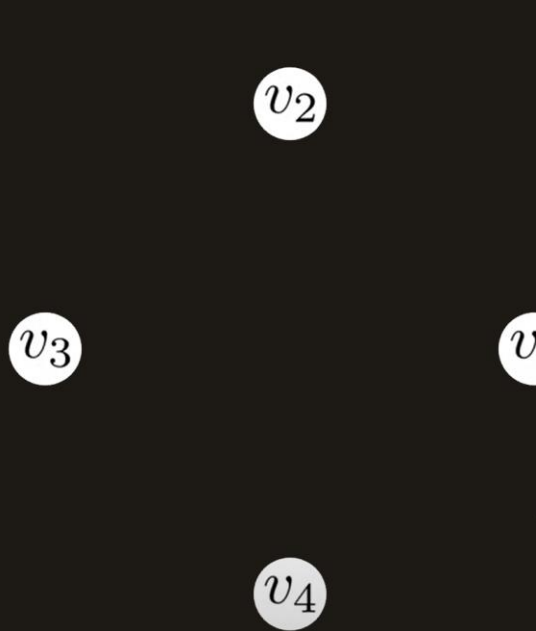
Observation 2: 0 is always an eigenvalue of  $L$ .

$$f(i) = f(j) \quad \forall i, j$$

Observation 3a: The smaller the eigenvalue, the *smoother* the eigenvector.

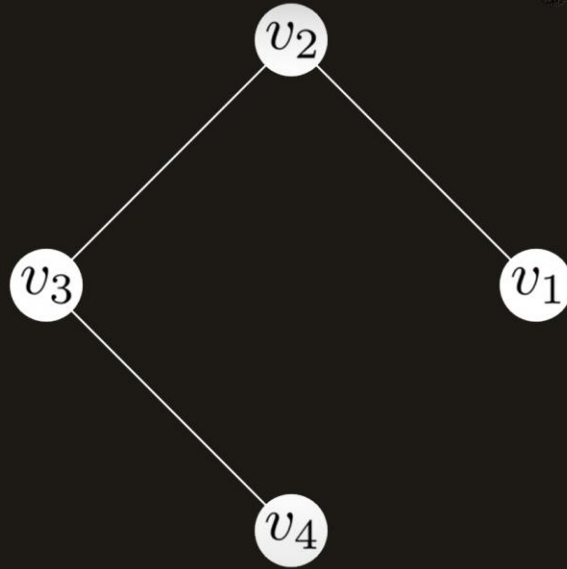
Observation 3b: The smaller the eigenvalue, the less *connected* the graph.

# Example: Disconnected Graph

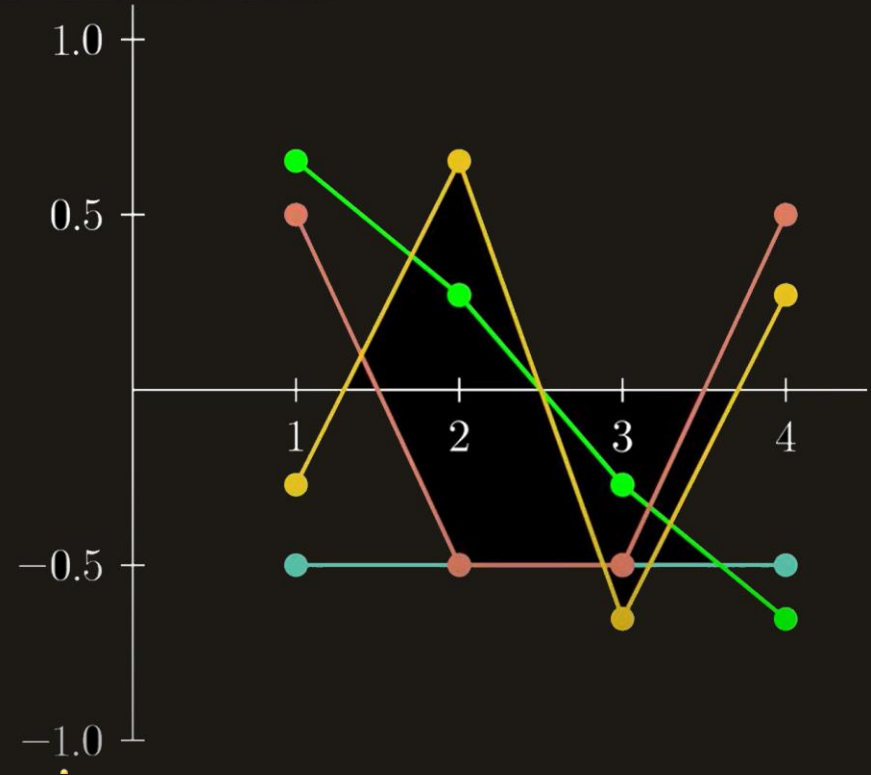

$$L = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$
$$\lambda = 0 \quad f_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad f_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad f_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad f_4 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$



# Example: Vertices in a Row



$$\begin{aligned}\lambda_1 &= 0 & \lambda_2 &= 0.59 \\ \lambda_3 &= 2.0 & \lambda_4 &= 3.41\end{aligned}$$



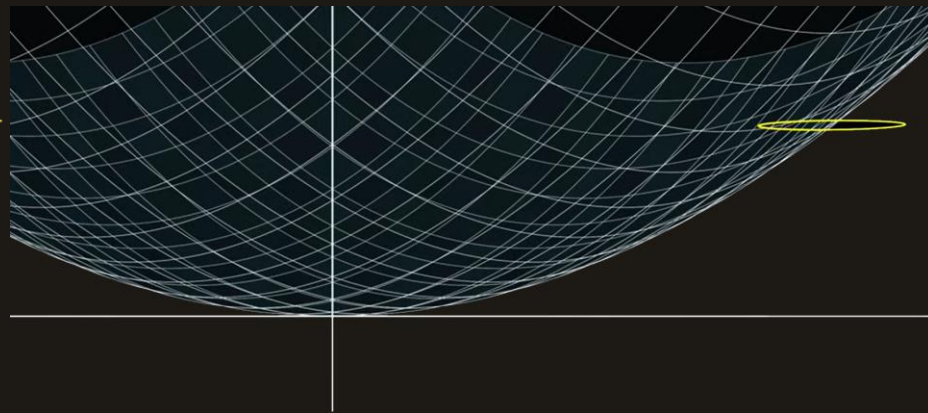
# Laplacian Operator

$$\nabla^2 f = \nabla \cdot \nabla f$$

$$\nabla^2 f(x) = \frac{d^2 f}{dx^2}$$

$$\nabla^2 f(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

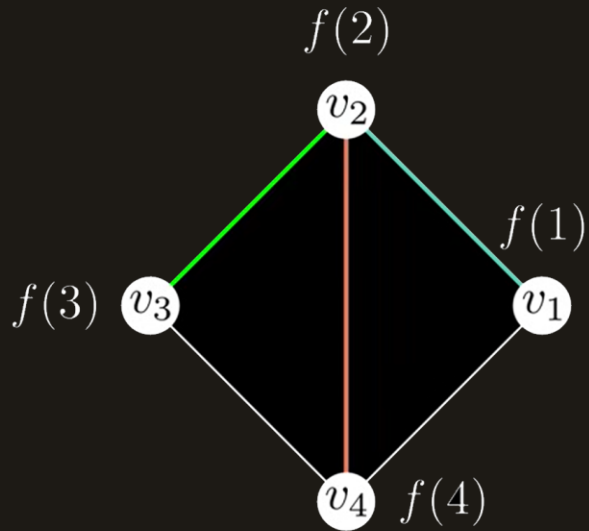
$$\nabla^2 f(x, y, z) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} + \frac{\partial^2 f}{\partial z^2}$$



$$\nabla^2 f(x, y) \geq 0$$

- **Laplacian operator calculates the divergence of a gradient in Cartesian coordinates**

# Why is it called the Laplacian matrix?



$$L = \begin{pmatrix} 2 & -1 & 0 & -1 \\ -1 & 3 & -1 & -1 \\ 0 & -1 & 2 & -1 \\ -1 & -1 & -1 & 3 \end{pmatrix}$$

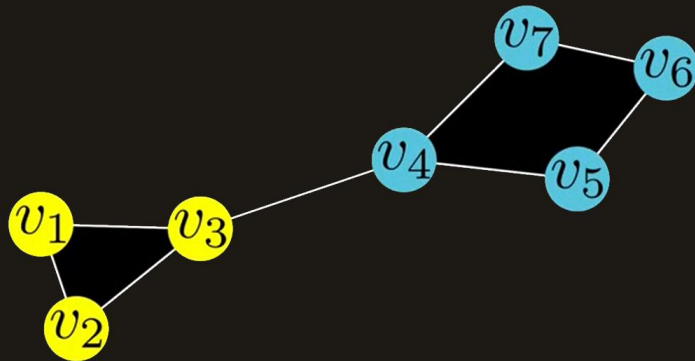
$$(Lf)_i = \sum_{j, i \sim j} (f(i) - f(j))$$

$$(Lf)_2 = (f(2) - f(1)) + (f(2) - f(3)) + (f(2) - f(4))$$

# An Application of Laplacian Matrix

**Theorem 1:** the Laplacian matrix  $L$  has an eigenvalue 0 with multiplicity  $k$  if and only if the graph has  $k$  connected components.

# Fiedler Value and Vector of a Graph



$$L = \begin{pmatrix} \boxed{\begin{matrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 3 \end{matrix}} & \begin{matrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{matrix} \\ \begin{matrix} 0 & 0 & \boxed{-1} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \boxed{\begin{matrix} 3 & -1 & 0 & -1 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ -1 & 0 & -1 & 2 \end{matrix}} \end{pmatrix}$$

$$f_2^T = \begin{pmatrix} 0.48 & 0.48 & 0.31 & -0.15 & -0.35 & -0.42 & -0.35 \end{pmatrix}$$

$$\lambda_2 = 0.36$$

# Applications of Laplacian Matrix

$$\lambda_k = \sum_{i < j, i \sim j} w_{ij} (f_k(i) - f_k(j))^2$$

$$f_2 = \operatorname{argmin}_f f^T L f, \text{ subject to } f^T \mathbf{1} = 0, f^T f = 1$$

$$f_3 = \operatorname{argmin}_f f^T L f, \text{ subject to } f^T \mathbf{1} = 0, f^T f_2 = 0, f^T f = 1$$

$$f_k = \operatorname{argmin}_f f^T L f, \text{ subject to } f^T \mathbf{1} = 0, f^T f_2 = 0, \dots, f^T f_{k-1} = 0, f^T f = 1$$

- **More generally looking for patterns in graph structure can be framed as an optimization problem with weights assigned to graph edges (weighted graph)**

# Spectral Embedding

## Principal Component Analysis

Dimension reduction

Only on *covariance* matrix

## Spectral Embedding

Graph partitioning

Works on any *similarity* matrix

On spectral clustering: Analysis and an algorithm

A Ng, M Jordan, Y Weiss

Advances in neural information processing systems 14

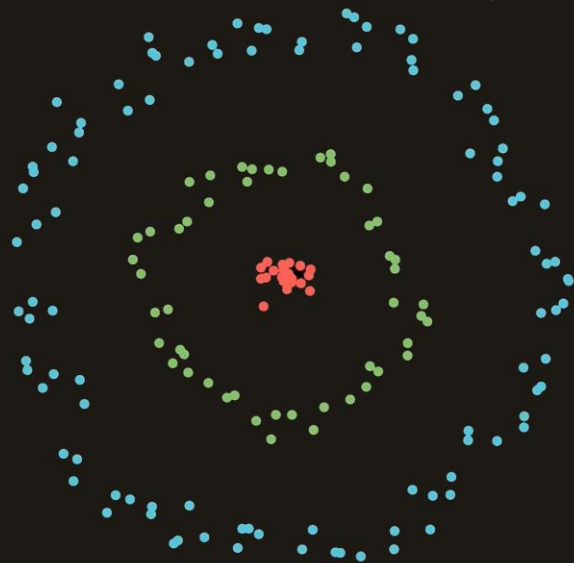
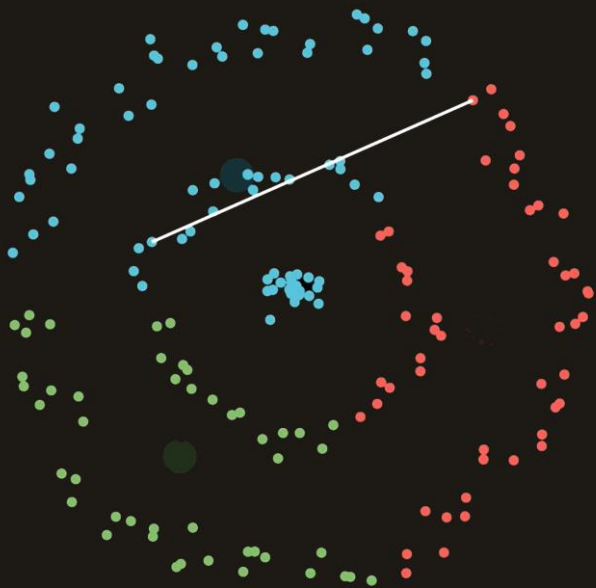
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# Spectral Clustering

$$A_{12} = \exp \left( - \underbrace{\frac{\|p_1 - p_2\|^2}{2\sigma^2}}_{\text{affinity between } p_1 \text{ and } p_2} \right)$$



# An Invitation to Spectral Graph Theory: Summary



- Graphs can be represented by matrices
- Graph eigenvectors and eigenvalues offer insight into its structure
- Graph Laplacian is a way to perform more complex graph analytics
- Spectral clustering is an application of Spectral Graph Theory in Machine Learning

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# THANKS!

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